A Personalized Learning Recommendation System Architecture for Learning Management System

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Abstract: The information on the web is ever increasing and it is becoming difficult for students to find appropriate information or relevant learning material to satisfy their needs. Technology Enhanced Learning (TEL) is an area which covers all technologies that improve students learning. Effective Personal Learning Recommendation Systems (PLRS) will not only reduce this burden of information overload by recommending the relevant learning material to the students of their interest, but also provide them with "right" information at the "right" time and in the "right" way. In this paper, we first present a detailed analysis of existing TEL recommendation systems and identify the challenges that exist for developing and evaluating the datasets. Then, we propose an architecture for developing a PLRS that aims to support students via a Learning Management System (LMS) to find relevant material in order to enhance student learning experience. Also we proposes a methodology for building our own collaborative dataset via learning management systems (LMS) and educational repositories. This dataset will enhance student learning by recommending learning materials from the former student's competence qualifications. The proposed dataset offer information on the usage of more than 19,296 resources from 628 courses apart from data from social learner networks (forums, blogs, wikis and chats), which constitutes another 3,600 stored files Finally, we also present some future challenges and a roadmap for developing TEL PLRSs.

1 INTRODUCTION

Technology Enhanced learning is the application of information and communication technologies to teaching and learning (Kirkwood and Price 2014). Recommendation Systems (RS) are software tools based on machine learning and information retrieval techniques (Aamir and Bhusry, 2015) that provide suggestions for potential useful items to someone's interest (Ricci et al., 2011). RSs' are widely used in many fields including TEL (Verbert et al., 2012). Until recent years Learning Management Systems (LMS), a subset of TEL, had not been personalized. Several researchers working in the field of LMS to enhance students learning experiences highlighted the need of RSs' for LMS, so as to address the following challenges in LMSs':

- Difficulty in sharing the learning resources;
- High redundancy of learning material (Shishehchi et al., 2011);
- Personalization of information (Fischer, 2011);
- Information overload (Manouselis et al., 2009)– which is the ever increasing volume of digital information particularly on the web, and due to this reason it has becomes extremely more and more difficult for learners to find suitable items to satisfy a particular need;
- Learning isolation.

Traditional LMSs only describe the basic information learning resources but could not describe the complex relationship between resources, teachers, students and their peers (Poorni et al., 2014). Also such systems could not integrate learning from formal, informal and social network learners (Fazeli et al., 2014).

This paper introduces a novel architecture for RS via LMS, Moodle in our case. Learning-related search problems are highly recurrent across a group of students participating in similar teaching activities. The process of discovering the optimal search query

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in a search engine like Google is repeated by all students participating in a particular module and the knowledge of the most optimal search query is not captured or shared across the community of students even though sharing this knowledge would significantly increase the learners' performance (Zaina et al., 2010). Recommendation systems in education filed should be personalized by the objectives of the task rather than on the preferences of students (Losada and Martín, 2014). Online social networks allow users to share ideas, activities, events, and interests within their contact network (Prates et al., 2013). This research project will prove the feasibility of using recommendation systems and social media applications in educational environments to deliver a working prototype of a recommender system that will assist the learner, and this implies learning from or reusing previous students querying experience, activity-based context which is based on users actions (Kramár and Bieliková, 2012), use of social media interactions among students. In section 2 we presents state-of-the art and current RSs' architectures and introduces personalized learning RS for TEL. In Section 3 we present the proposed PRS architecture. Section 4 presents the Datasets for TEL RSs' and associated challenges. Section 5 presents the challenges in evaluating the RSs' for TEL. Finally section 6 presents conclusions and direction for future work.

2 STATE OF THE ART AND CURRENT RS ARCHITECTURES FOR TEL

2.1 Recommendation Systems

There has been massive growth in research on RSs' and the applications of RSs to various areas in the last 15 years (Candillier et al., 2009). The following are the commonly proposed approaches for building RSs':

2.1.1 Content based Filtering

Content based RSs' predict an item to a user based on the similarity between the items content description and the user's preferences model (Pazzani and Billsus, 2007). Content based RSs' work with user and item profiles which were referred in the past. The referred profiles are represented as vectors, which hold the characterizing attributes of items or users. (del Losada and Martín, 2014) has developed a Prototype of Content-Based RS in an Educational Social Network. The experiments were carried on in a real time environment ClipIt (elgg, 2016) tool. However, the recommendations generated are uniform for all the students and lacks personalization. To enhance students learning experience (Hsu, 2008) has developed an online personalized English learning RS which facilitates English as a Second Language (ESL) student with reading lessons that suit individual student preferences.

2.1.2 Collaborative Filtering

Collaborative filtering techniques are most commonly used in social networking and social media environments for proposing user interactions or interesting shared resources (Karampiperis et al., 2014). Collaborative RSs' aims to predicts individual preferences and provide suggestions for links for further resources or other systems, products and resources which are likely to be of interest. (Dascalu et al., 2015) developed an educational collaborative filtering recommender agent (U Learn) with a build-in integrated learning style recommender. Such RS helps in providing suggestions and shortcuts for learning materials and learning tools, helping the learner to better navigate through educational resources. The limitation of such RS are recommendations made by the learners with similar learning styles.

2.1.3 Knowledge based Filtering

Knowledge-based RSs integrate the user knowledge, items or products in order to provide recommendations. This filtering technique mark the items for recommendations based on historical data information, which is followed by the development of an information recommender by using logical reasoning technology (Burke, 2002). (Manouselis et al., 2011; Zaina et al., 2011 and Zapata et al., 2013) highlighted the need of RSs for TEL based on a literature review which focuses on the availability and ever increasing quantity of digital learning resource repositories and from the outcomes of Social Information Retrieval for Technology Enhanced Learning (SIRTEL) annual workshop series and a Special Issue on Social Information Retrieval for TEL and proposed a DELPHOS and e-LORS (e-learning object recommender system) which are integral and intelligent solution for the recommendation of learning objects (LO) stored in a repository in which the recommendation are provided in an ordered list of LOs'.

2.1.4 Hybrid Filtering

Hybrid RSs involve are the combination of collaborative filtering and content-based filtering techniques. (Adomavicius and Tuzhilin, 2005; Gu, 2013; Manouselis et al., 2012; Ricci et al., 2011) (Ricci et al., 2011) suggest four different types of hybrid recommenders: Separate collaborative and content-based RSs; Collaborative RSs with added features of content-based filtering method; Content-based RSs with added features of collaborative filtering method. (Poorni et al., 2014) presents a personalized e-learning hybrid RS using the concept of “Fuzzy Tree Matching” by considering the key factors such as 1) learning activities and learners’ profiles 2) learning activities and 3) pedagogical issues. (He et al., 2014) proposed A Social Recommender System called as SRSH based on Hadoop parallel computing platform. SRSH system integrates content-based and collaborative filtering techniques to further improve the performance of recommendation. (Khribi et al., 2012) presents a framework for building automatic recommendations in e-learning platforms which consists of two modules: an off-line module and an online module. The first module pre-processes the data to build user and content models. Online module uses these models dynamically to find the user’s requirement and goals, and predicts a list of recommendation. User preferences objects are obtained by using a “range of recommendation strategies” which are primarily based on hybrid (content-based filtering and collaborative filtering) filtering approach.

2.2 Personalized Learning RSs

Why personal? Every user, students in our case, has individual needs and particular requirements. Some of the students are highly self-motivated and learn by exploring while other students prefer some specific guidance in a structured way. With the ever growing computer and internet technologies available, many universities use LMSs’ to support teaching and learning. Presently many LMSs’ are available as proprietary solutions and open source (Santos and Boticario, 2011). Despite the diversity in term of core functionalities, these LMSs’ share a few commonalities such as calendar, files, storage, forums, wikis, blogs, etc. Education learning systems, in particular LMS can further improve teaching and learning practices of learners if supported by personalized recommendations (Hauger and Köck, 2007) and accessibility issues (Moreno et al., 2009). The research finding in (Dagger et al., 2007) shows that future LMSs’ primarily focus on service-oriented architectures to incorporate social media aspects into LMSs’.

3 A PROPOSED LMS PRS ARCHITECTURE

In this section we present the proposed architecture for a LMS recommendation system for recommending learning material to students, which is the primary objective of this paper. We selected Moodle LMS in this case. The proposed architecture is given in “Figure:1” and it consists of three main components ‘learning material data source’, ‘seeking student information’, and ‘generation’.

‘Learning material data source’ component is the primary data source and this component is the building block for designing and building our own dataset for this research project. The dataset developed here constitutes the knowledge base of both formal and informal learners. The output of this component is the preprocessed data which is collected from:

- MEC(Middle East College) Moodle Database - former students competence qualifications;
- Social Learners Network - wikis, forums, blogs @ MEC LMS;
- Other institutes LMS Servers. i.e., other three institutes in Oman.

The recommendation from all the above can take hybrid filtering technique though well-defined educational metadata sources and educationally influenced filtering decisions. The methodology given in (Karampiperis and Diplaros, 2007) will be applied, which generate a matrix to represent the educational attributes of the learning resources. The recommendation from all the above can take hybrid filtering technique though well-defined educational metadata sources and educationally influenced filtering decisions. Additional filtering process can be applied on this matrix based on an educational “footprint” followed by the learners of these three data sources.

The data acquired from MEC Moodle and LMS of other institutes, connected using state of the art “mutual authentication technology” which uses Transport Layer Security protocol (Sheffer et at., 2015), consist of formal learning data as well as informal learning data acquired through social learners’ networks.

Pre-processing of data allows the original data from the above three sources to be transformed into a

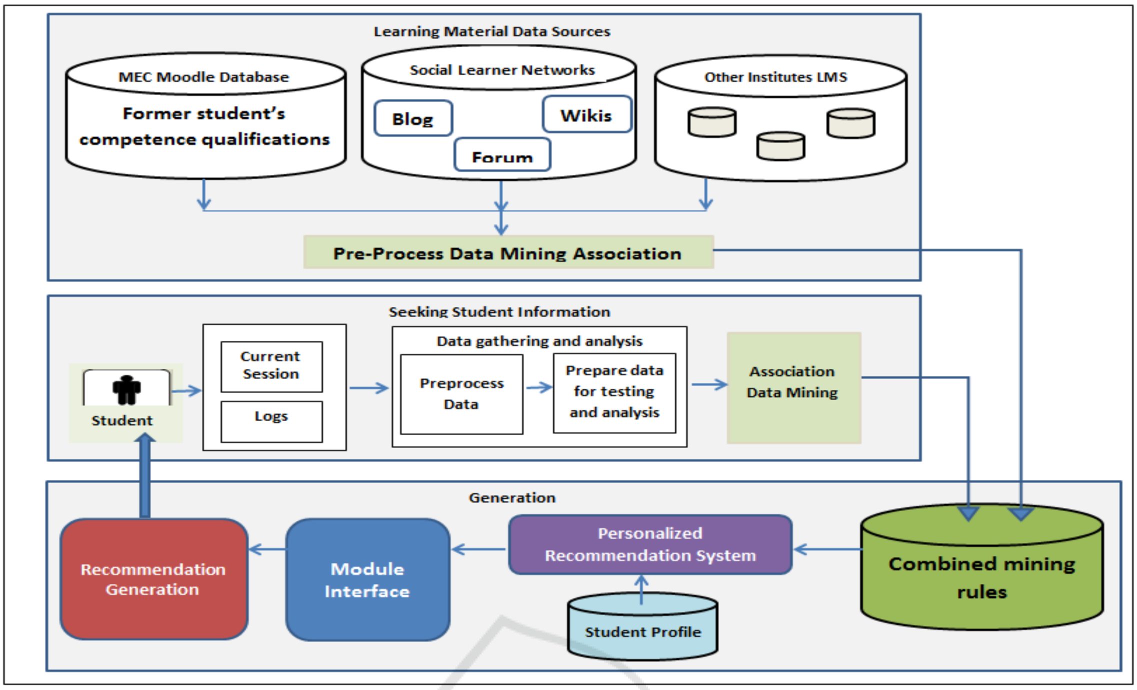

Figure 1: Proposed architecture of a Personalized Recommendation System.

suitable form to be used by a data mining association algorithm. The data pre-processing tasks in this component includes data filtering, year and semester wise session identification, student profiling, path completion, transaction identification, data transformation and enrichment, data integration, data reduction to generate an explicit learning experience.

'Seeking student information' component represents the various characteristics of the student, including students profile creation, that can be used to generate an implicit learning experience using the data mining association rules. This involves understanding the "learning material attributes", which can be obtained from student's current Moodle session or previous logs of the student in social learner network. Building student requirements cannot be justified only by precise values, but also a multi-criteria analysis approach need to be applied. This is done by developing a multi criteria decision model using linear weighted sum or a more rigorous approach based on fuzzy set technology. The student preferences and learning behavior can be defined using the following three steps:

1. Clicks: This action defines the shortlisting of material.
2. Selection: This action is defined as material selected and added to cart.
3. Learning: This action is using or reading the material.

The above three behaviors are used to identifying the learners relative preferences LP_{ij} for each of the material referred from the data sources. The formula used is:

$$LP_{ij} = \frac{LP_{ij}^{c} - Min_{1\le j\le |M|}\left(LP_{ij}^{c}\right)}{Max_{1\le j\le |M|}\left(LP_{ij}^{c}\right) - Min_{1\le j\le |M|}\left(LP_{ij}^{c}\right)} + \frac{LP_{ij}^{s} - Min_{1\le j\le |M|}\left(LP_{ij}^{s}\right)}{Max_{1\le j\le |M|}\left(LP_{ij}^{s}\right) - Min_{1\le j\le |M|}\left(LP_{ij}^{s}\right)} + \frac{LP_{ij}^{l} - Min_{1\le j\le |M|}\left(LP_{ij}^{l}\right)}{Max_{1\le j\le |M|}\left(LP_{ij}^{l}\right) - Min_{1\le j\le |M|}\left(LP_{ij}^{l}\right)}$$

LP_{ij}^{c}, LP_{ij}^{s} and LP_{ij}^{l} denotes the number of references to material through clicks, selection and learning actions made by the learner i for material j respectively. $Max_{1\le j\le |M|}\left(LP_{ij}^{c}\right)$, $Max_{1\le j\le |M|}\left(LP_{ij}^{s}\right)$ and $Max_{1\le j\le |M|}\left(LP_{ij}^{l}\right)$ denotes the maximum number of clicks, selection and learnings for a learner i for M material. $Min_{1\le j\le |M|}\left(LP_{ij}^{c}\right)$, $Min_{1\le j\le |M|}\left(LP_{ij}^{s}\right)$ and $Min_{1\le j\le |M|}\left(LP_{ij}^{l}\right)$ denotes the minimum number of clicks, selection and learnings for a learner i for M material.

The first stage of the 'Generation' component is to apply data mining rules and techniques on the outputs of 'learning material data source' and ‘seeking student information’ components and forward the results to a Hybrid RS. The objective of this is to model students’ information seeking behavior in order to develop a personalized information retrieval system to enhance students’ learning experiences and such a PRS must have the features given below. Students’ profile database has the logs and records of learning styles, learning material access and other profile of student with respect to his/her specialization. These records and logs will be used to identify the student’s preferences with peers.

Some feature of educational RSs are suggested in (López et al., 2015) and includes: monitoring behavior, heuristics to infer information, user feedback, filtering rules, navigation history, internal database of items, similarity matching. The proposed PRS will have the following features:

- Good user interface design;
- Real time recommendation as a service;
- Accuracy of identifying student requirements;
- Structured and accurate finding of recommended learning materials;
- Implicit and explicit recommendation of learning material.

4 DATASETS FOR TEL RECSYS

In the last decade many researches have development RSs for TEL but only a few of them validated these RSs based on real time scenarios (Dascalu et al., 2015). (Drachsler et al., 2010; Manouselis et al., 2010) raises the issue of missing data sets for recommender systems in TEL that can be used as benchmarks to compare different recommendation approaches. The availability of datasets helps in drawing stronger conclusions about the validity and generalizability of scientific experiments. This also helps researchers to compare the experimental results based on large datasets that capture learner interactions in real settings. Furthermore, educational datasets can support research advances on TEL towards a basic theory for TEL (Verbert et al., 2011) by offering the recorded and observed behaviour of the stakeholders (students, teachers, parents, lifelong learners, educational institutes) in different formal and informal learning settings. (Verbert et al., 2011) suggested guidelines for assembling suitable datasets. We proposed a framework for building our own dataset, “Figure: 2”, for the RS architecture given in “Figure: 1”. The building of proposed dataset framework is based on the guidelines given in (Verbert et al., 2011) which include:

a. Create a data set that realistically reflects the variables of the learning setting”;
b. “Use a sufficiently large set of user profiles”;
c. “Create data sets that are comparable to others”.

5 EVALUATING TEL RSS

An evaluation of an interactive system ensures that it behaves as expected by the designer and that it meets the requirements of the user (Dix, 2009). (Ricci et al., 2011) has provided some evaluation requirements of TEL RSs and has proposed a four layer general guidelines framework to evaluate the success of TEL RSs: 1. Reaction of user, 2. Learning, 3. Behaviour, 4. Results. (Thai-Nghe et al., 2010) presented a protocol for used for TEL RSs evaluation. The evaluation algorithms were implemented in MyMedia open source framework and the results were compared with traditional methods such as logistic regression or linear regression. (Drachsler et al., 2009) highlighted the limitations that exists in the evaluation of TEL RS due to unavailability of datasets. They also suggested the framework given in Table 1 for the analysis of TEL RSs.

Table 1: (adapted from (Drachsler et al., 2009)): An evaluation framework for RSs in TEL.

Measurements	Parameters
Technical measures	1. Accuracy 2. Performance
Educational measures	1. Effectiveness 2. Efficiency 3. Satisfaction
Social network measures	1. Variety 2. Centrality

6 CONCLUSIONS AND FUTURE WORK

In this paper we have presented a study of evaluations of recommendation systems for TEL by raising several concerns, issues and challenges encountered by these systems. We also proposed a personalized learning material recommendation system architecture and discuss related technologies.

The proposed architecture has good characteristics in recommending students to choose appropriate learning materials for their assessments

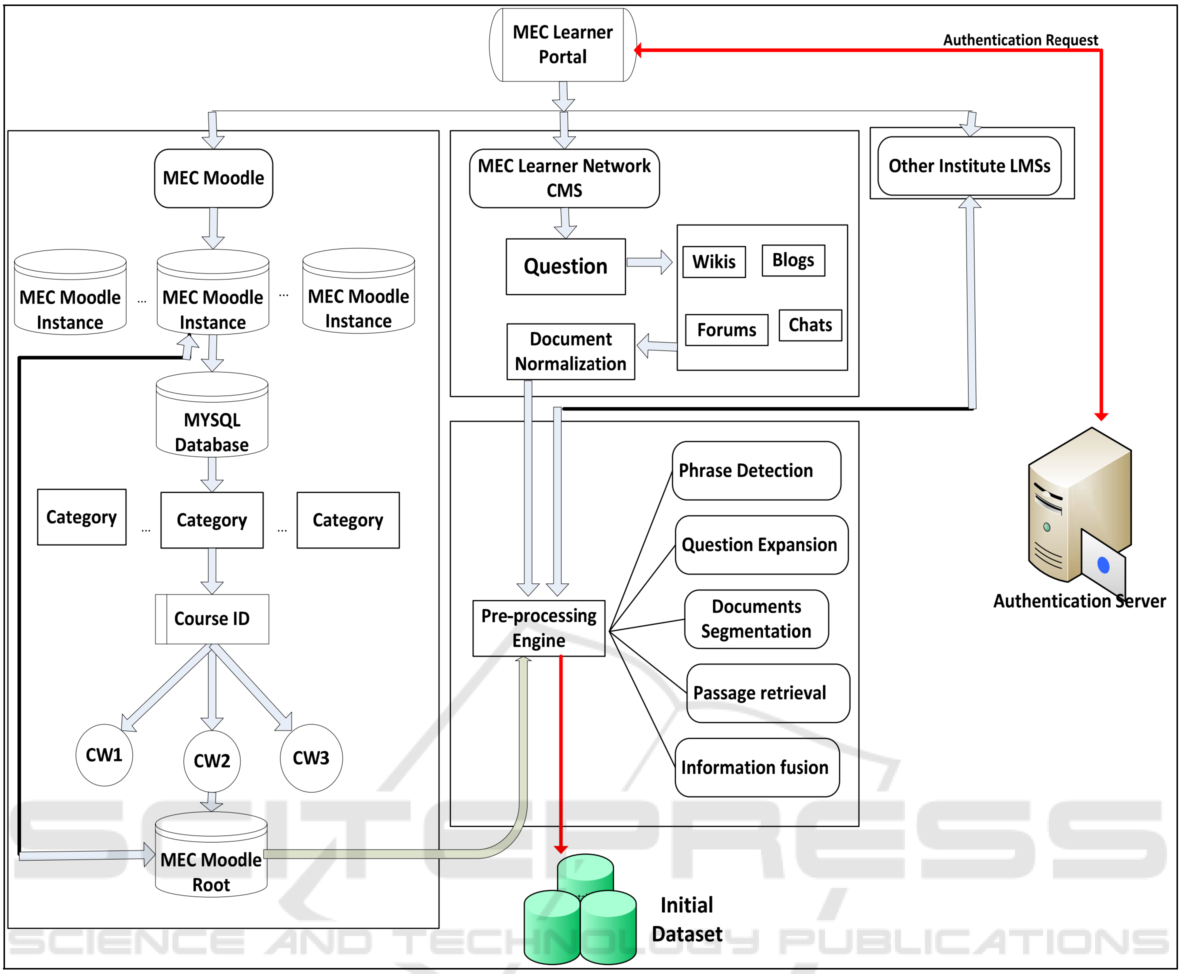

Figure 2: Architecture building dataset for personalized material recommendation system.

by providing relevant recommendations. In the next phase of this research project the framework will be implemented as a plugin for the MEC Moodle to be tested and validated, but not limited to, on the newly developed dataset.

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